

Comparison of LDA and Topical Methods in Topic Modeling Against Emotion Labels on Twitter Data #Indonesiagelap

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Abstract

This study analyzes public discussions on Twitter regarding the #IndonesiaGelap hashtag to identify emotional patterns and major topics in socio-political discourse. A total of 10,866 tweets were collected and processed through standard preprocessing steps. Text representation was performed using TF-IDF and Sentence Transformer, which served as inputs for topic modeling with LDA and BERTopic. Emotion detection using EmoSense-ID revealed a dominance of negative emotions—particularly *sadness*, *anger*, and *disgust*—indicating widespread public concern and dissatisfaction. LDA produced 10 topics with an average coherence score of 0.342, while BERTopic identified 39 topics with generally higher coherence, demonstrating its ability to capture more nuanced subthemes. Cosine similarity evaluation further showed that embedding-based representations effectively captured semantic closeness among tweets. Overall, this study provides a concise yet comprehensive overview of public perceptions surrounding #IndonesiaGelap through combined emotion and topic modeling approaches.

Keywords: (NLP, Emotion, LDA, BERTopic, Twitter, Indonesia.)

INTRODUCTION

Social media has become a primary channel for sharing and receiving information due to its wide reach and rapid dissemination, influencing public opinion on social, political, and governmental issues (Kusumaningsih, 2024)(Kusumaningsih, 2024). One rapidly growing platform is Twitter, where users share information, views, and emotions about various current events (Suparto, 2021). Digital expressions on Twitter can serve as an analytical source to understand the evolving perceptions and sentiments of the public (Tirtopangarsa & Maharani, 2021).

The hashtag #IndonesiaGelap emerged as an expression of public dissatisfaction particularly among younger generations regarding perceived instability in social and economic conditions (Mufidah & Haliq, 2025). This sentiment is linked to criticism of policies introduced during the first 100 days of the Prabowo Subianto and Gibran Rakabuming Raka administration, which some young people view as unfavorable to the public. The hashtag serves as a representation of a “dark” and concerning situation and can be analyzed to understand the public’s social and psychological responses to ongoing issues (Clairine et al., 2025).

Emotion analysis and topic modeling are text-analysis approaches used to gain insights into language-based data. Emotion analysis identifies various emotional states expressed by individuals, such as happiness, sadness, or anger (Khairani et al., 2024). Meanwhile, topic modeling uncovers hidden themes within large text corpora and groups them into coherent topics. Combining these methods helps researchers understand not only what the public is discussing but also how they feel about those topics (Puspita et al., 2024).

Commonly used topic modeling algorithms for identifying patterns and topic structures in large document collections, as well as for analyzing research trends, are Latent Dirichlet Allocation (LDA) and BERTopic (Defit & Sovia, 2024).

The principle of LDA is that each document in a corpus is a mixture of hidden topics, with each topic represented by a probability distribution of words. The dominant topic is determined by the words with the highest probabilities (Nuradilla et al., 2025). In contrast, BERTopic leverages the semantic representation of text to create vectors that capture the meaning of each document (Wahyuni et al., 2025).

In addition to identifying topics, this study also examines the relationship between emotions and public conversation themes by measuring semantic similarity and the quality of the generated topics (H et al., 2025).

Previous studies have demonstrated the effectiveness of topic modeling and sentiment analysis methods. (Husna et al., 2024) applied LDA to iconic speeches, successfully revealing key topics such as freedom, human rights, and social justice along with the orators' sentiments. (Khalid et al., 2023) combined LDA and Naïve Bayes to analyze mental health sentiment during the Covid-19 pandemic, finding that this combination accurately mapped topics and public sentiment trends. (Mohanna & Basiouni, 2024) employed BERTopic to examine YouTube comments on AI, highlighting the complexity of consumer perceptions and the prevalence of negative emotions due to system biases. (Anugrah & Agatha, 2025) used IndoBERT and BERTopic to analyze public opinions on BPS Instagram posts, identifying key issues of distrust in poverty data and appreciation for statistical data quality. Meanwhile, (Defit & Sovia, 2024) compared LDA and BERTopic in analyzing computer science research trends, showing that BERTopic produced more coherent and relevant topics, reflecting a shift toward data analytics and intelligent technology themes.

Based on previous studies, most research has focused on applying LDA and BERTopic to identify topics and public sentiment trends, yet few have integrated topic modeling with emotion classification. Therefore, combining emotion analysis with topic modeling is needed to gain a more comprehensive understanding of the emotional orientation of each emerging topic (Nawar, 2024).

RESEARCH METHOD

This study employs a combination of Natural Language Processing (NLP), traditional and modern text representations, and both probabilistic and embedding-based topic modeling methods. This approach aims not only to identify emotions expressed within the text but also to capture the primary topics emerging from public discourse.

As illustrated in Figure 1, the research process consists of several sequential steps. First, data was collected through social media crawling. Next, preprocessing was performed to ensure clean and consistent text suitable for analysis. The emotion detection stage then classified each tweet into its corresponding emotional category. Text representation was generated using two approaches, TF-IDF and Sentence Transformer, which served as the foundation for topic modeling using LDA and BERTopic. Finally, model performance was evaluated using Coherence Score and Cosine Similarity to ensure that the resulting topics were stable, coherent, and relevant to the content of the dataset.

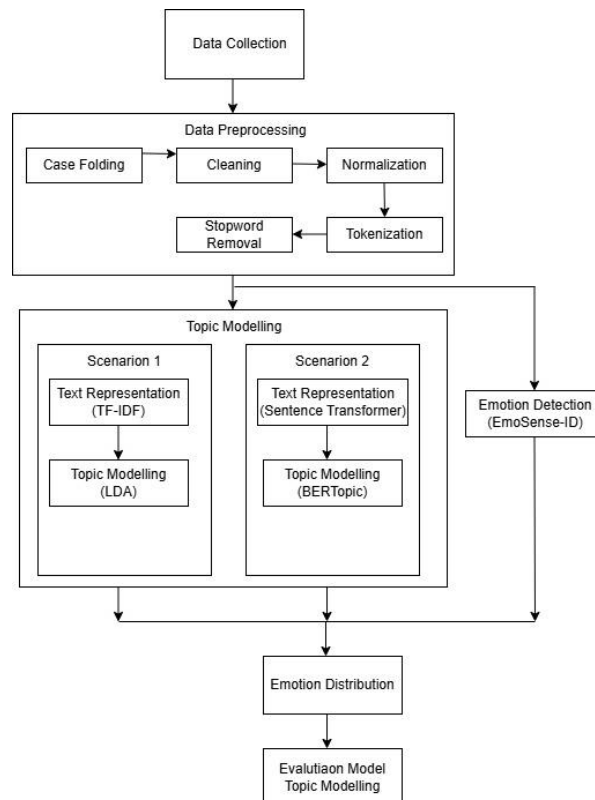


Figure 1. Research Stages

Data Collection. The data collection stage involved extracting text from Twitter using the #IndonesiaGelap hashtag, which contains expressions, opinions, and concerns from the public particularly younger users regarding perceived instability in social, economic, and political conditions. This hashtag serves as a public critique of government policies and a space for expressing dissatisfaction and hopes for the country. Data crawling was conducted from February to October 2025, yielding 10,866 tweets. The raw data then underwent preprocessing and language normalization to prepare it for subsequent analysis, including emotion detection, text representation, and topic modeling.

Data Preprocessing. The preprocessing stage prepares the crawled Twitter text for analysis. Raw Twitter data typically contains irrelevant elements such as emojis, excessive punctuation, URLs, mentions, and informal language, so it must be cleaned and normalized beforehand. The preprocessing process in this study includes several steps. First, case folding converts all characters to lowercase. Second, cleaning removes URLs, mentions, emojis, and unnecessary symbols. Third, normalization is applied to standardize non-formal words, abbreviations, and slang commonly found in Twitter conversations. The text is then split into tokens through tokenizing, followed by stopword removal to eliminate common words that do not contribute to the analysis. The final step is stemming, which reduces words with affixes to their base form. These steps produce cleaner and more structured text, ready for emotion analysis, text representation, and topic modeling.

Text Representation. The text representation stage transforms the preprocessed and emotion-labeled data into numerical formats suitable for topic modeling algorithms. This study employs two different representation approaches each aligned with the specific topic modeling method used.

The first approach is TF-IDF (Term Frequency-Inverse Document Frequency), which serves as the representation basis for topic modeling using LDA. TF-IDF assigns weighted importance to each word by comparing its frequency within a document to its frequency across

the entire corpus, producing a frequency-based matrix well-suited for statistical methods such as LDA.

The second approach is Sentence Transformer, which generates dense embeddings as the text representation for BERTopic. This transformer-based model captures contextual and semantic relationships between sentences more effectively, resulting in richer and more informative embeddings appropriate for embedding-based topic modeling.

Topic Modeling. Topic modeling is applied to identify the main themes emerging from Twitter conversations using the #IndonesiaGelap hashtag. Two complementary approaches, Latent Dirichlet Allocation (LDA) and BERTopic are employed to obtain a more comprehensive understanding.

The first approach, LDA, relies on probabilistic word distributions within documents. Texts are represented using TF-IDF matrices, enabling the model to detect frequently co-occurring words and form topics based on their distribution patterns.

The second approach, BERTopic, utilizes embedding-based modeling. Sentence Transformer is used to generate semantic-rich sentence vectors, which are then clustered into coherent topics and enhanced with representative keywords. Using both methods allows the study to compare topic quality and characteristics, providing a richer and more informative analysis.

Emotion Detection. The emotion detection stage aims to identify the emotional content expressed in each preprocessed tweet. This study employs EmoSense-ID, a transformer-based model for Indonesian text capable of recognizing eight basic emotions defined by Plutchik: joy, trust, fear, surprise, sadness, disgust, anger, and anticipation. Cleaned tweets are fed into the model to predict their emotional category, enabling the analysis of public emotional responses surrounding the #IndonesiaGelap issue. The output of this stage is an emotion label for each tweet, which is then used for subsequent processes such as text representation and topic modeling.

Emotion Distribution. This section describes how emotion labels are mapped to topics generated by LDA and BERTopic. Each tweet's classified emotion is used to analyze its distribution across topics, showing not only the main themes but also the associated emotional tendencies. This provides insight into public responses to the #IndonesiaGelap issue, highlighting topics dominated by negative or positive emotions.

Evaluation. The evaluation stage ensures that LDA and BERTopic models effectively represent topic structures. Three approaches are applied: Coherence Score, to assess semantic consistency within topics; Cosine Similarity, to measure text vector similarity and prevent overlapping topics; and emotion distribution analysis, to examine the spread of users' emotional responses across topics. Together, these methods evaluate topic quality, relevance, and the models' effectiveness in reflecting public issues and perceptions related to #IndonesiaGelap.

RESULTS AND DISCUSSION

This section presents the results obtained from the analysis and discusses the findings in detail, highlighting their implications in relation to the research objectives.

Data Collection. The data collection process resulted in a total of 10,866 tweets containing the hashtag #IndonesiaGelap, representing a wide range of public expressions related to social, economic, and political concerns. Data crawling was conducted from February to October 2025, yielding a diverse set of tweets characterized by informal language, abbreviations, hashtags, and context-dependent commentary. Examples of the collected raw text are presented in Table 1.

Table 1. Data Tweet

No	Text
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1	@KompasTV iya diinjeksi pewarna yg RON90 jd RON92.... permainan kata ² dan cuma pengalihan isu aja pdhl apa susahnya minta maaf dan bertanggungjawab #indonesiagelap
2	@mejiyaaa_ @crustaceaspp @starfess Endingnya bahasa #IndonesiaGelap
3	@AlternativeA117 @parttimerant Nggak pernah lihat r/Indonesia cemooh Prabowo dan dukung tuntutan #IndonesiaGelap?
4	@pakmul63 Usut tuntas #adilijokowi #IndonesiaGelap
5	@prabowo ayo #AdiliJokowi Finalis Koruptor Dunia #IndonesiaGelap gara gara dipimpin @jokowi Cc @DPR RI @Gerindra

Data Preprocessing. The preprocessing stage was applied to transform the raw Twitter text into a clean and structured corpus suitable for analysis. As shown in Table 2, the process consisted of several key steps: case folding, cleaning, normalization, tokenization, and stopword removal. These steps removed noise such as URLs, mentions, emojis, and informal expressions, while standardizing words into consistent forms. The resulting preprocessed text provided a refined dataset ready for emotion detection, text representation, and topic modeling.

Table 2. Data Preprocessing

No	Text
1	iya diinjeksi pewarna yang ron jadi ron permainan kata ² pengalihan isu saja padahal susahnya maaf bertanggungjawab indonesia gelap
2	endingnya bahasa indonesia gelap
3	tidak lihat r indonesia cemooh prabowo dukung tuntutan indonesia gelap
4	usut tuntas adili jokowi indonesia gelap
5	ayo adili jokowi finalis koruptor dunia indonesia gelap gara gara dipimpin cc

Text Representation. Term Frequency–Inverse Document Frequency (TF–IDF) method was applied to convert the preprocessed tweets into numerical vectors that reflect the importance of each word within a document. TF–IDF assigns higher weights to terms that are unique or highly specific to a particular tweet while appearing less frequently across the corpus, making it effective in highlighting key terms relevant to each document. The table below presents the highest-weighted terms from selected documents as generated by the TF–IDF computation.

Table 3. TF–IDF Representation

No	Tweet	Kata Teratas (TF–IDF)	Bobot
1	1	ron	0.491081
2	1	diinjeksi	0.342017
3	1	pewarna	0.327572
4	1	kata ²	0.309374
5	1	susahnya	0.297386

The results presented in Table 3 show that the highest TF–IDF–weighted terms in Document 1 are “ron,” “diinjeksi,” “pewarna,” “kata²,” and “susahnya.” These terms receive high weights because they are prominent within the specific tweet while being relatively rare across the entire dataset, making them strong indicators of the document’s main context.

Text Representation. Sentence Transformer model to generate dense semantic embeddings for each tweet. This method produces high-dimensional vector representations that

capture contextual meaning rather than relying on word frequency. The resulting embeddings provide a richer representation of semantic relationships and are used as input for the BERTopic modeling process.

Table 4. Sentence Transformer Representation

No	Tweet	dim_1	dim_2	dim_3	dim_4	dim_5
1	1	0.020644	0.004706	-0.032609	0.037892	0.036004
2	2	0.080528	-0.006512	-0.001891	0.032204	0.037983
3	3	0.036507	0.096477	0.004188	-0.035776	-0.028512
4	4	0.078998	0.021214	0.001206	0.020055	0.025820
5	5	-0.004745	0.078377	-0.052330	-0.035318	0.061130

Table 4 presents a subset of the embedding vectors generated by the Sentence Transformer for the first five tweets. Each tweet is represented as a high-dimensional real-valued vector (384 dimensions), where each dimension encodes a specific aspect of contextual meaning learned by the model. The variation across dimensions indicates that each tweet has a distinct semantic representation. For example, Tweet 1 has a negative value in dimension 3 (-0.032609) but a positive value in dimension 4 (0.037892), reflecting nuanced meaning encoded by the model. This pattern demonstrates the ability of Sentence Transformer embeddings to encode deeper contextual and emotional cues.

Topic Modeling. Before interpreting the LDA output, the optimal number of topics was determined using the coherence score, which measures the semantic consistency among the top words within each topic. Higher coherence values indicate more meaningful and interpretable topics. Multiple configurations were tested, ranging from 1 to 10 topics. Table 4 results show that the model achieved its highest coherence score at 10 topics, with a value of 0.4337. Therefore, the number of topics used in the LDA model was set to 10 topics.

Table 5. Best topic LDA

No	Topic	Coherence Score
1	1	0.3278
2	2	0.3485
3	3	0.3734
4	4	0.3745
5	5	0.3050
6	6	0.3511
7	7	0.3452
8	8	0.3673
9	9	0.3664
10	10	0.4337

Table 6. LDA Topic

No	Topic	Label	Keywords
1	1	Politik & Indonesia Gelap	indonesia, gelap, hati, selamat, hasil, jaga, perlawanan, result, pengeluaran, pemenang
2	2	Protes & Demo Rakyat	indonesia, gelap, rakyat, tidak, negara, demo, pemerintah, bikin, bener

No	Topic	Label	Keywords
3	3	Kekerasan & Aparat	nyawa, the, acab, tujuan, fasilitas, hilang, hancur, musuh
4	4	Polisi & Media	polisi, bayar, media, oknum, pemerintah, gabisa, aspirasi, bungkam
5	5	Korupsi & Ekonomi	omon, ocrp, kabinet, harga, pertamina, koruptor, dunia
6	6	Politik & Kekerasan Online	melek, anarkis, politik, silenced, kekerasan, negatif
7	7	Media Sosial & Hoaks	indonesia, gelap, tiktok, tipu, kejadian
8	8	Isu Publik & Administrasi	safe, temen, plese, palsu, jabatan, ruu, tunjangan
9	9	Hukum & Keamanan	mati, koruptor, hukum, kampus, menang, aturan
10	10	Politik & Korupsi	indonesia, gelap, jokowi, negara, adili, korupsi, presiden

Table 5 and Table 6, presents the LDA topic modeling results along with manually assigned thematic labels. Overall, the topics are dominated by themes of politics, public protests, state criticism, police violence, and corruption, all of which align with the narrative associated with the hashtag #IndonesiaGelap. Topics 1 and 2 revolve around the phrase “indonesia gelap,” reflecting collective dissatisfaction and negative public sentiment. Topics 3 and 4 include terms such as *acad*, *police*, *media*, *bungkam*, indicating discussions about law enforcement and state violence. Topics 5 and 10 highlight corruption and economic issues, shown through words like *koruptor*, *kabinet*, *pertamina*, *adili*. Other topics capture conversations about social media activity, administrative issues, and public security. These results suggest that LDA effectively captures the underlying thematic structure of the discourse, revealing strong socio-political criticism embedded within the tweets.



Figure 2. LDA Topic Word Clouds

Word cloud visualization for each topic generated by the LDA model. The word clouds highlight the dominant keywords within each topic, where larger words represent higher

contribution or relevance. This visualization supports thematic interpretation of the extracted topics.

Topic Modeling. The BERTopic model generated 39 topics automatically based on semantic clustering of the tweets. To improve interpretability, each topic was manually assigned a thematic label derived from its dominant keywords.

Table 7. BERTopic Topic

No	Topic	Count	Label	Main Words
1	1	1401	Indonesia Gelap Naik	gelap, indonesia, naikin, trussss, berisik, adili, jokowi, prabowo, tidak, selamat
2	2	818	Korupsi & Koruptor	korupsi, koruptor, kuadriliun, era, slamat, korup, indonesia, gelap, negara, pejabat
3	3	488	Uang & Pajak	uang, pajak, rakyat, bayar, bank, anggaran, duit, miskin, negara, yang
4	4	388	polisi, bayar, media, oknum, pemerintah, gabisa, aspirasi, bungkam	politik, yukk, meleak, rakyat, pemerintah, yang, indonesia, gelap, demokrasi, negara
5	5	286	Politik & Pemerintah	omon, ocrp, kabinet, harga, pertamina, koruptor, dunia
6	6	271	Demo & Aksi	tagar, demo, indonesia, gelap, suara, aksi, rakyat, teman, kampanye, twitter
7	7	266	Penipuan & Kejahatan	mulyondol, tolol, tipu, orang, jurus, gelap, tidak, indonesia, yang, saja
....	...	...	...	...
38	38	12	Kucing & Macan	kucing, macan, biaya, lu, taik, jdi, budi, baacoottt, danantoro, gurihnya
39	39	12	Kejahatan & Investigasi	kejahatan, investigasi, jurnalistik, berfokus, narkoba, finansial, pencucian, penyalahgunaan, terorganisir, perdagangan

Table 7. represnted that BERTopic results reveal that discussions within the #IndonesiaGelap hashtag are largely shaped by intertwined political, economic, and social concerns. High-frequency topics highlight widespread public dissatisfaction with national conditions, particularly involving corruption, government leadership, and economic pressure. Conversations surrounding public policies, presidential performance, and political dynamics appear prominently, indicating that political discontent forms the core of the discourse. In addition, several topics reflect more focused societal issues such as taxation, public demonstrations, fraud, and criminal incidents, which are perceived as indicators of broader systemic problems.



Figure 3. BERTopic Topic Word Clouds

The BERTopic word cloud is used to visualize the dominant keywords within each topic generated by the model. Unlike a general word cloud that reflects corpus-wide word frequency, this visualization represents semantically clustered keywords derived from BERTopic's automatic topic generation. The size of each word corresponds to its contribution to the topic, providing a clearer view of the thematic structure and supporting the interpretation of topic semantics.

Compared to LDA, BERTopic identifies a larger and more diverse set of topics. This is due to its embedding-based clustering mechanism, which captures finer semantic distinctions between texts. As a result, themes that may appear merged within a single LDA topic can be separated into more specific and granular topics in BERTopic. These findings indicate that BERTopic is more sensitive to contextual variations within the discourse, producing a richer and more detailed topic structure.

Emotion Detection. The emotion detection stage produces an emotion label for each preprocessed tweet. Table X presents sample prediction results, showing several tweets along with their corresponding emotion categories as identified by the model.

Table 8. Emotion Detection

No	Text	Predicted emotion
1	iya diinjeksi pewarna yang ron jadi ron permainan kata? pengalihan isu saja padahal susahnya maaf bertanggungjawab indonesia gelap	Disgust
2	endingnya bahasa indonesia gelap	Sadness
3	tidak lihat r indonesia cemoooh prabowo dukung tuntutan indonesia gelap	Anger
4	usut tuntas adili jokowi indonesia gelap	Anger
5	ayo adili jokowi finalis koruptor dunia indonesia gelap gara gara dipimpin cc	Anger

From Tabel 8, anger and disgust appear as the most prominent emotions, reflecting strong criticism, dissatisfaction, and condemnation toward government actions and national issues. The presence of sadness indicates expressions of disappointment or pessimism within the discourse surrounding #IndonesiaGelap. Overall, the emotional pattern suggests that the

hashtag is largely driven by intense negative sentiments, highlighting public concern and frustration over the discussed socio-political conditions.

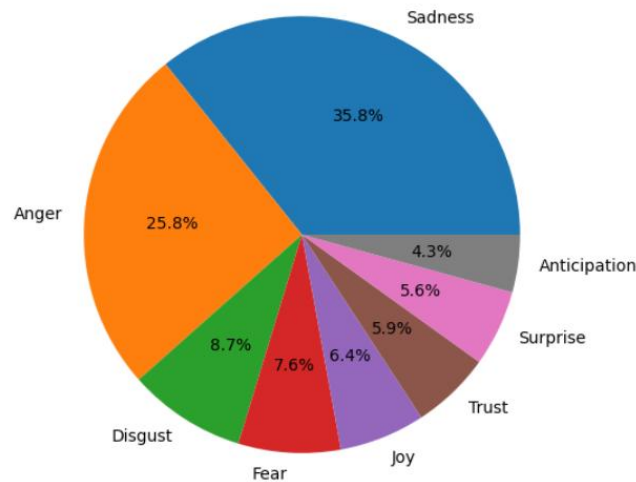


Figure 4. Emotion Detection Pie Chart

The emotional distribution reveals that discussions under the *#IndonesiaGelap* hashtag are heavily dominated by negative emotions. Sadness appears as the most frequent emotion (35.8%), indicating widespread disappointment and concern. Anger follows at 25.8%, reflecting strong public dissatisfaction and frustration. Other negative emotions such as disgust, fear, and surprise also appear in smaller proportions, suggesting a complex yet predominantly critical emotional response. Positive emotions like joy and trust are minimal, showing that the overall sentiment of the conversation is largely negative.

Emotion Distribution. The distribution of emotions across each LDA topic was analyzed to see how people's emotional responses were distributed across specific themes. The following table presents the total emotion scores for each topic, followed by a stacked bar graph visualizing the proportion of emotions present for each topic.

Topik	Disgust	Sadness	Anger	Trust	Fear	Joy	Anticipation	Surprise
1	27.046900	220.271957	78.222824	17.093287	29.037630	187.001511	25.233303	24.249128
2	402.225189	1173.095215	972.263855	192.533875	300.868378	159.123062	172.585449	275.410950
3	23.691593	113.621338	61.863708	15.450659	18.081390	17.955162	9.418170	15.793056
4	32.886131	143.183517	104.094330	23.388470	36.223114	15.610366	16.447744	23.476036
5	23.389952	98.909111	72.070961	16.565498	34.141075	18.562666	8.998591	15.189601
6	17.124054	89.259605	59.269081	29.417845	18.207552	12.811004	12.765973	13.938976
7	49.018658	238.689835	142.414246	22.775925	97.498100	42.262749	28.038319	34.015358
8	32.950024	131.552551	102.301346	24.780760	35.345505	20.909172	22.436876	25.482094
9	26.486788	93.435730	63.493118	13.157152	23.764385	13.761162	8.960906	15.304365
10	285.858734	1527.092285	1064.493286	262.030762	208.520935	184.090073	143.385040	155.829056

Figure 5. Emotion distribution LDA

Figure 5 shows that Topics 2 and 10 had the highest emotional scores across almost all categories, particularly sadness and anger. This indicates that these two topics address the most sensitive issues or trigger strong emotional reactions. Lower-scoring topics, such as Topics 3, 5, and 6, indicate lighter conversations or those less likely to trigger intense emotional responses. Overall, sadness and anger dominated most topics, reinforcing the finding that discourse under *#IndonesiaGelap* is rife with public criticism and disappointment.

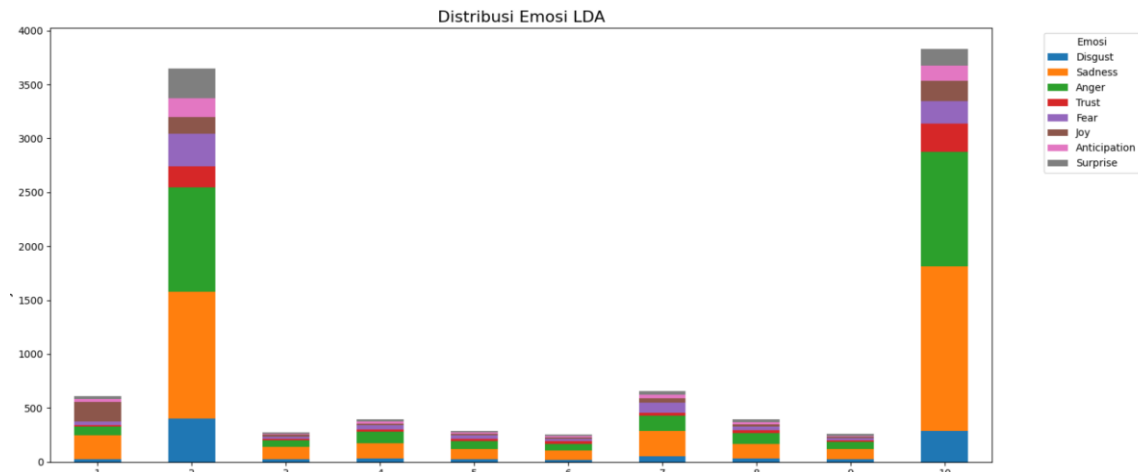


Figure 6. Stacked Bar Emotion Distribution LDA

The stacked bar graph shows that Topic 2 and Topic 10 have a significantly higher number of emotions than the other topics. These two topics exhibit a predominance of negative emotions, particularly sadness and anger. While some other topics show a more balanced distribution of emotions, their intensity remains much lower.

The emotional distribution analysis of the BERTopic results aims to observe the emotional tendencies within each generated topic. Although BERTopic identified 39 topics in total, this section highlights the first 7 topics with the highest document counts as a representative overview of the emotional patterns.

Topik	Disgust	Sadness	Anger	Trust	Fear	Joy	Anticipation	Surprise
1	82	758	154	38	138	107	40	84
2	114	247	281	52	36	21	25	42
3	24	117	168	69	35	27	31	16
4	40	130	118	27	27	12	14	20
5	20	69	95	54	13	13	13	9
6	20	116	54	14	21	11	15	20
7	45	55	118	7	14	3	10	14

Figure 7. Emotion distribution BERTopic

Figure 7, show that emotion Sadness and Anger dominate most topics, especially Topic 1, which contains the highest volume of tweets. This suggests that discussions within #IndonesiaGelap are strongly colored by sadness and anger. Other emotions such as Fear, Disgust, and Surprise appear moderately, while Joy, Trust, and Anticipation remain relatively low. This pattern indicates that the issue triggers predominantly negative emotional responses.

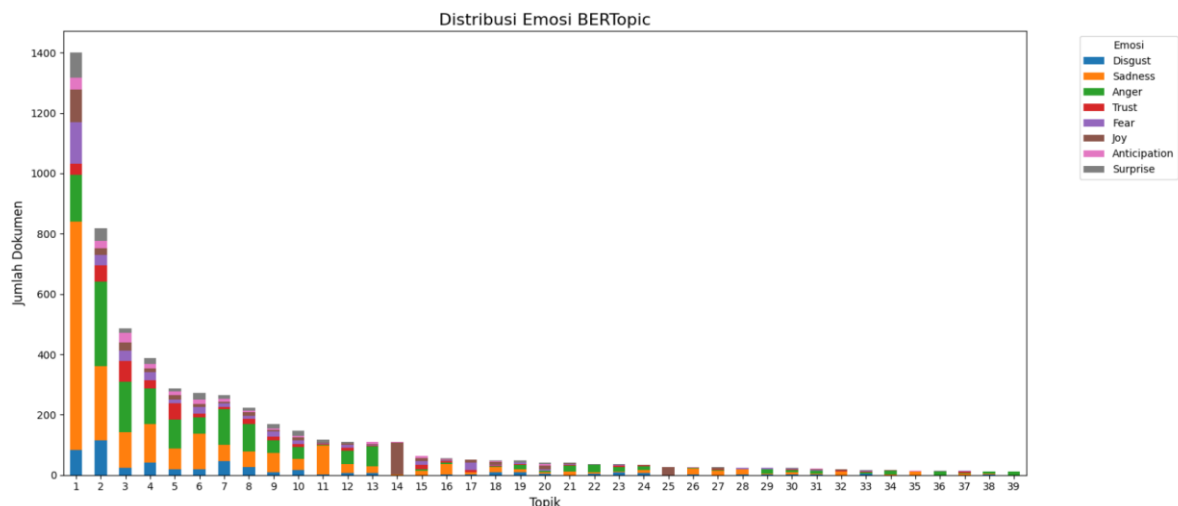


Figure 8. Stacked Bar Emotion Distribution BERTopic

Figure 8, illustrates that Topic 1 contains the highest emotional intensity, driven mainly by Sadness. Topics 2 and 3 also show strong amounts of Anger and Sadness, while later topics display smaller yet consistent emotional patterns.

Evaluation. Coherence evaluation is conducted to assess the quality of the topics generated by the LDA model. The coherence score reflects how semantically related the words within a topic are. Higher values indicate that the topic is more interpretable and the words are more meaningfully connected.

Topik 1: Coherence = 0.279
 Topik 2: Coherence = 0.502
 Topik 3: Coherence = 0.472
 Topik 4: Coherence = 0.242
 Topik 5: Coherence = 0.327
 Topik 6: Coherence = 0.287
 Topik 7: Coherence = 0.289
 Topik 8: Coherence = 0.213
 Topik 9: Coherence = 0.393
 Topik 10: Coherence = 0.413

Figure 8. Coherence Score LDA

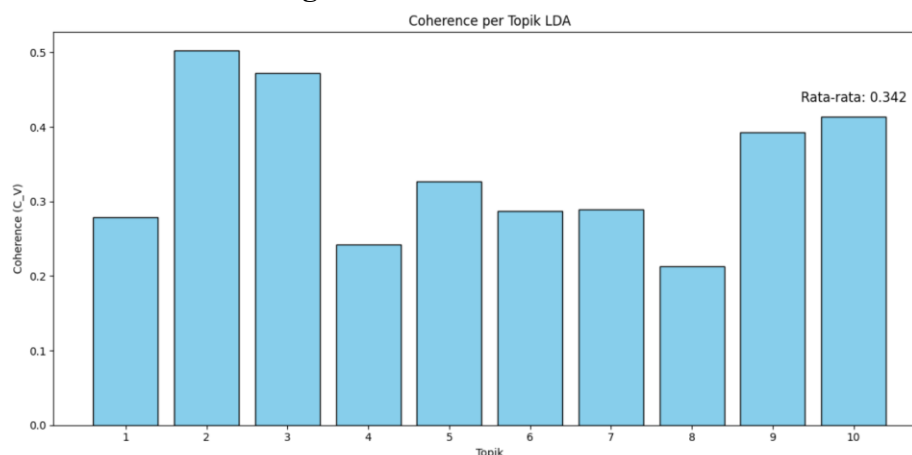


Figure 9. Bar Chart Coherence Score LDA

Figure 8 and Figure 9, the evaluation shows that LDA coherence scores range from 0.213 to 0.502, with an average of 0.342. Topic 2 (0.502) and Topic 3 (0.472) have the highest

coherence, indicating strong semantic consistency and better interpretability. Meanwhile, Topic 8 (0.213) has the lowest score, suggesting weaker word cohesion. Overall, the average score of 0.342 indicates that the topic quality is moderately good, though some topics require improvement for better semantic clarity.

The coherence evaluation for BERTopic measures how well each topic is formed based on the semantic similarity of the words within that topic. Higher coherence values indicate that the words are strongly related and represent a clear thematic structure.

Topik 1 → Coherence: 0.312	Topik 21 → Coherence: 0.372
Topik 2 → Coherence: 0.283	Topik 22 → Coherence: 0.467
Topik 3 → Coherence: 0.335	Topik 23 → Coherence: 0.281
Topik 4 → Coherence: 0.466	Topik 24 → Coherence: 0.304
Topik 5 → Coherence: 0.346	Topik 25 → Coherence: 0.985
Topik 6 → Coherence: 0.395	Topik 26 → Coherence: 0.355
Topik 7 → Coherence: 0.395	Topik 27 → Coherence: 0.364
Topik 8 → Coherence: 0.504	Topik 28 → Coherence: 0.223
Topik 9 → Coherence: 0.254	Topik 29 → Coherence: 0.332
Topik 10 → Coherence: 0.420	Topik 30 → Coherence: 0.381
Topik 11 → Coherence: 0.314	Topik 31 → Coherence: 0.441
Topik 12 → Coherence: 0.344	Topik 32 → Coherence: 0.240
Topik 13 → Coherence: 0.324	Topik 33 → Coherence: 0.312
Topik 14 → Coherence: 0.927	Topik 34 → Coherence: 0.381
Topik 15 → Coherence: 0.513	Topik 35 → Coherence: 0.984
Topik 16 → Coherence: 0.663	Topik 36 → Coherence: 0.959
Topik 17 → Coherence: 0.997	Topik 37 → Coherence: 0.997
Topik 18 → Coherence: 0.553	Topik 38 → Coherence: 0.368
Topik 19 → Coherence: 0.199	Topik 39 → Coherence: 0.999
Topik 20 → Coherence: 0.289	

Figure 10. Coherence Score BERTopic

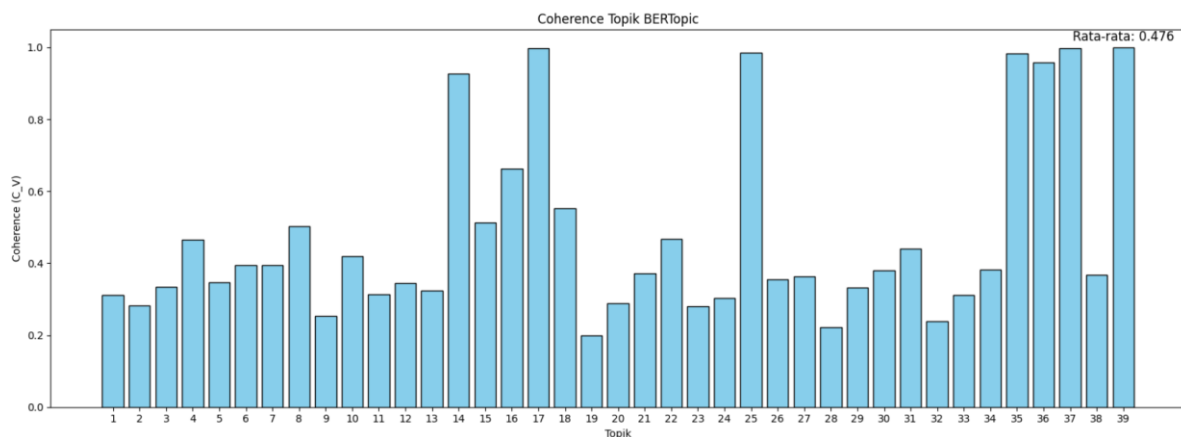


Figure 11. Bar Chart Coherence Score BERTopic

Figure 10 and Figure 11, the coherence evaluation of BERTopic reveals a wide range of values across the 39 generated topics. Several topics achieve extremely high coherence scores, nearing 1.0, such as topics 17, 25, 35, and 39, indicating strong semantic consistency and clearly defined thematic structures. Other topics, including topics 14, 16, 18, and 15, also show high coherence, suggesting stable and interpretable themes. Many topics fall within the medium coherence range (0.30–0.46), meaning their semantic consistency is adequate but not as robust. Meanwhile, a few topics, such as topics 19 and 28, exhibit low coherence, reflecting weaker thematic cohesion.

The cosine similarity that show at Figure 12, calculation produced a matrix of (10865 × 10865), indicating that all tweets were compared pairwise to measure semantic similarity. For example, the similarity between document 0 and document 1 is 0.63, suggesting a moderate semantic overlap. The nearest neighboring documents to document 0 show even higher similarity scores, ranging from 0.77 to 0.79, with a value of 1.0 for the document itself. These results demonstrate that the text representation model effectively captures semantic relationships across tweets. The presence of highly similar document pairs indicates recurring patterns or themes in the dataset, which strengthens the reliability of the subsequent topic modeling and emotion analysis processes.

```
Shape matrix: (10865, 10865)
Contoh similarity dokumen 0 dan 1: 0.6328189452342029

Dokumen paling mirip ke-0: [ 0 6824 10722 2435 9458 4972]
Nilai similarity: [1. 0.79044725 0.78529585 0.78156009 0.77710961 0.77525007]
```

Figure 12. Cosine Similarity Score

Distribution topic, the LDA model illustrates how all tweets are allocated into ten generated topics. Each topic contains information on the number of assigned documents, its coherence value, and the proportion of the eight emotional categories. This distribution helps reveal dominant emotional patterns within topics and assess the thematic quality.

Topik	Count	Coherence	Prop_Disgust	Prop_Sadness	Prop_Anger	Prop_Trust	Prop_Fear	Prop_Joy	Prop_Anticipation	Prop_Surprise
1	607.6635131835938	0.2786914616163979	0.04451021924614906	0.36219489574432373	0.12873011827468872	0.028119513764977455	0.04770343378186226	0.30722808837890625	0.041525378823280334	0.039906121790401
2	3649.3681640625	0.5021616065466237	0.11021663248538971	0.322552889585495	0.26602432131767273	0.052510879933834076	0.08230186253786087	0.04364684224128723	0.047264475375413895	0.07546835392713
3	275.8835144042969	0.4720243367647665	0.08587561547756195	0.411842942237854	0.2240903079509735	0.056004539132118225	0.06554018706083298	0.06508104503154755	0.034138422425936394	0.057245675474401
4	395.4894104003906	0.24241260811225557	0.08315358310937881	0.3621986508369446	0.2635596692562103	0.059137292206287384	0.09141508489847183	0.03946239873766899	0.04158797487816539	0.059358950704336
5	287.9691467285156	0.3268319990308506	0.08122458308935165	0.3438378572463989	0.25027433037757874	0.057522810995578766	0.11834805458784103	0.06446076184511185	0.03140733763575554	0.05275054648518
6	252.60597229003906	0.28672192509535116	0.06778939813375473	0.3529603183269501	0.23409515819277954	0.11645082384347916	0.0720784068107605	0.05071508511900902	0.050532057881355286	0.05518092215061
7	653.8136596679688	0.2888631582620524	0.07497473061084747	0.36407172679901123	0.21818599104881287	0.03483409434556961	0.1491205394268036	0.0642869845032692	0.04242365434765816	0.05202571675181
8	396.4975280761719	0.21335779270568023	0.08310288190841675	0.3317471146583557	0.2584093511104584	0.06249771639704704	0.08926546573638916	0.05273446813225746	0.05658770352602005	0.06426829099655
9	258.36346435466875	0.3927440782374629	0.1025177612900734	0.3614468574523926	0.24575106799602509	0.05092482641339302	0.0919807106256485	0.053262945264577866	0.03468649461865425	0.05923569202423
10	3831.537353515625	0.4131547227649882	0.07460752129554749	0.3977263271808624	0.27810484170913696	0.06862442195415497	0.05459129437804222	0.04814639315009117	0.03751663863658905	0.04068954553127

Figure 13. Distribution Topic LDA

The LDA distribution reveals that certain topics, particularly Topics 1, 2, and 10, contain significantly more tweets, suggesting these issues are the most widely discussed within the *#IndonesiaGelap* discourse. Emotionally, most LDA topics are dominated by sadness and anger, reflecting the critical and negative public sentiment toward socio-political conditions. Coherence scores vary, with topics such as Topic 4 and Topic 10 displaying stronger thematic consistency. Overall, the LDA model forms reasonably focused topics, although some remain emotionally mixed.

Distribution topic, BERTopic displays how tweets are spread across 39 topics, with only a few topics containing large volumes while many others consist of relatively small tweet counts. BERTopic provides a more fine-grained segmentation compared to LDA, resulting in more specific thematic divisions.

Topik	Count	Coherence	Prop_Disgust	Prop_Sadness	Prop_Anger	Prop_Trust	Prop_Fear	Prop_Joy	Prop_Anticipation	Prop_Surprise
1	1401	0.311920	0.058530	0.541042	0.109921	0.027123	0.098501	0.076374	0.028551	0.059957
2	818	0.283197	0.139364	0.301956	0.343521	0.063570	0.044010	0.025672	0.030562	0.051345
3	488	0.334893	0.049180	0.239754	0.344262	0.141393	0.071721	0.055328	0.063525	0.032787
4	388	0.465873	0.103093	0.335052	0.304124	0.069588	0.069588	0.030928	0.036082	0.051546
5	286	0.345984	0.069930	0.241259	0.332168	0.188811	0.045455	0.045455	0.045455	0.031469
6	271	0.395095	0.073801	0.428044	0.199262	0.051661	0.077491	0.040590	0.055351	0.073801
7	266	0.394965	0.169173	0.206767	0.443609	0.026316	0.052632	0.011278	0.037594	0.052632
8	223	0.503813	0.121076	0.228700	0.412556	0.071749	0.040359	0.058296	0.026906	0.040359
9	169	0.253840	0.053254	0.384615	0.242604	0.065089	0.106509	0.035503	0.029586	0.082840
10	146	0.420183	0.116438	0.246575	0.267123	0.068493	0.095890	0.054795	0.041096	0.109589
11	117	0.314338	0.017094	0.811966	0.025641	0.017094	0.017094	0.025641	0.008547	0.076923
12	111	0.344335	0.063063	0.252252	0.414414	0.081081	0.099099	0.027027	0.018018	0.045045
13	111	0.324342	0.063063	0.189189	0.594595	0.036036	0.027027	0.009009	0.063063	0.018018
14	111	0.926779	0.000000	0.009009	0.000000	0.000000	0.009009	0.954955	0.018018	0.009009
15	63	0.513180	0.000000	0.222222	0.079365	0.222222	0.222222	0.126984	0.126984	0.000000
16	56	0.663316	0.053571	0.589286	0.107143	0.071429	0.053571	0.017857	0.071429	0.035714
17	52	0.997173	0.038462	0.115385	0.000000	0.153846	0.480769	0.173077	0.038462	0.000000
18	48	0.553473	0.166667	0.375000	0.083333	0.020833	0.041667	0.229167	0.062500	0.020833

Figure 14. Distribution Topic BERTopic

BERTopic produces a distribution skewed toward several large topics—such as Topics 1, 2, 3, and 4 while most remaining topics contain only a small number of tweets. This pattern is typical for BERTopic due to its embedding-based clustering, which captures subtle semantic variations. Emotional patterns similarly highlight sadness, anger, and fear as dominant categories, though BERTopic provides more detailed emotional proportions. The presence of many small-sized topics indicates that BERTopic effectively identifies fine-grained subthemes, but requires careful manual interpretation.

CONCLUSION

This study demonstrates that social media text analysis can effectively reveal public perceptions on sensitive issues such as #IndonesiaGelap. Emotion detection results indicate the dominance of negative sentiments—*sadness*, *anger*, and *disgust*—signaling widespread concern, frustration, and dissatisfaction among the public toward socio-political conditions in Indonesia. In topic modeling, LDA produced fewer, more general themes, while BERTopic generated a larger number of more fine-grained and nuanced topics. Coherence evaluation shows that both models are valid, although BERTopic offers higher thematic consistency in several clusters. The cosine similarity analysis further confirms that embedding-based representations can group semantically similar tweets effectively. Overall, this research provides a comprehensive thematic and emotional mapping of public discourse and highlights the potential of NLP approaches in understanding large-scale societal opinions.

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